Prediction and elasticities

Key concepts & study plan

Experimental design

Data collection & processing

Model specification & estimation

Interpretation & application

Estimation *vs* prediction

Estimation

- represents step of *understanding* current behaviour
- find best model parameters

Prediction

- how will behaviour change under given scenario?
- e.g. some products are added/removed/changed
- involves applying estimated model, not reestimating it on changed data

Prediction and elasticities

The basics of forecasting

- Apply estimated model to:
  - predict choices in **new** settings
  - predict impact of **changes** in products
  - predict impact of **changes** in population
- Mainly relevant in labelled settings

Prediction and elasticities

Forecasting matters

- Many studies are primarily interested in willingness-to-pay
- Even then, useful diagnostic check to look at forecasts
- For example, does estimated model give reasonable implied elasticities?
- Well fitting models do not necessarily lead to good forecasts!
- Substantial risk of over-fitting to estimation data

Prediction and elasticities

How do we produce forecasts?

- Use estimated β to calculate V_{jn} and P_{jn} for all n and j

	parameter	Apple iPhone	Samsung Galaxy	Huawei P
δ_{Apple}	2.5	1	0	0
$\delta_{Samsung}$	0.75	0	1	0
$\beta_{features}$	0.2	8	4	2
β_{price}	-0.01	600	400	350
	V	-1.9	-2.45	-3.1
	e^V	0.1496	0.0863	0.0450
	P	53.24%	30.72%	16.04%

Question:

What is chosen?

Prediction and elasticities

Assigning choice to Apple ignores probabilistic nature

	Apple iPhone	Samsung Galaxy	Huawei P
V	-1.9	-2.45	-3.1
P	53.24%	30.72%	16.04%

- Use average P_j across N instead of individual-level predictions
- Or assign choice according to P_j
  - In our case, take a random draw $0 <= r_U <= 1$
    - if $r_U <= 0.5324$, choose Apple iPhone
    - if $0.5324 < r_U <= 0.8396$, we choose Samsung Galaxy
    - if $0.8396 < r_U$, we choose Huawei P
- Try `deterministic_vs_probabilistic.xlsx` for a mode choice example

Impact of changes

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Impact of changes

Studying the impact of a change in cost

- Carry out prediction with increased cost and get new predicted choices/demand
- Might seem reasonable to compare to base cost choices in data
- Would mean comparing a modelled outcome to an observed outcome
  - model outcomes are affected by error, while data is not
  - model is not likely to perfectly reproduce base scenarios
    - except for linear-in-parameters MNL with full set of ASCs

Impact of changes

Solution

- Make two predictions from model
  - Baseline prediction: apply model without changing attributes/population
  - Forecast prediction: apply model with changed data
- Can then compare forecast to baseline application
- Both are affected by the same model bias

Impact of changes

Elasticities

- Elasticity is percent change in probability as a result of change in an attribute

Own elasticity of MNL

$$E_{i,x_{k,i}} = \frac{\partial V_i}{\partial x_{k,i}} x_{k,i} \left(1 - P_i\left(\beta\right)\right),$$

with linear in attributes V, $\frac{\partial V_i}{\partial x_{k,i}} = \beta_{x_k}$

Cross-elasticity of MNL

$$E_{i,x_{k,j}} = -\frac{\partial V_j}{\partial x_j} x_{k,j} P_j\left(\beta\right),$$

exhibiting *IIA* characteristic

Much more complex for advanced models

Impact of changes

Elasticities: arc elasticity approach

Baseline application

- predicted share for product i: $S_{i,base}$

Forecast prediction

- apply same increase (e.g. cost) for whole sample, say $\Phi_C = \frac{C_{i,new}}{C_{i,base}}$, e.g. $\Phi_C = 1.01$
- obtain new share for product i: $S_{i,forecast}$

Elasticity calculation

- Calculate $E_{i,C} = log\left(\frac{S_{i,forecast}}{S_{i,base}}\right)/log(\Phi_C)$
- See `elasticities.xlsx`

Impact of changes

Marginal effects

- Approach used especially with categorical variables
- Compare predicted demand at two different levels of a given variable
- Could also use with continuous variables
- Can use for attributes of alternatives, characteristics of decision-makers, etc
- Approach:

Prediction 1: Make prediction of demand with variable of interest set to first level of interest for entire data: $D_{j,1} = \sum_n \sum_t P_{jnt}\left(x_{jnt} = L_1\right)$

Prediction 2: Make prediction of demand with variable of interest set to second level of interest for entire data: $D_{j,2} = \sum_n \sum_t P_{jnt}\left(x_{jnt} = L_2\right)$

Comparison: Compute $\frac{D_{j,2} - D_{j,1}}{D_{j,1}}$

Corrections to constants and scale

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Corrections to constants and scale

Correcting market shares

- Market shares in estimation sample may be very different from real world market shares
- Can recalibrate the model by adjusting the alternative specific constants
- Let δ_j^0 be the the estimated constant for alternative j before correction, with S_j^0 being the market share predicted by the uncorrected model
- Let S_j^R be the real world market share
- Constants can be adapted to: $\delta_j^1 = \delta_j^0 + log\left(\frac{S_j^R}{S_j^0}\right)$
- Iterative process which can require a few steps
- See `asc_correction.xlsx`

Corrections to constants and scale

Correcting the scale

- Scale especially in SP data may be very different from real world scale
- Ideally, this can be corrected through joint RP-SP estimation
- But RP data might not always be available
- Compute implied cost elasticity with estimated coefficients
- Compare elasticity with expectations or official guidelines
- Then adjust the scale until the two are in line
- See `scale_correction.xlsx`

Forecasting in practice

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Forecasting in practice

Care is required

- Need to consider whether the estimated model is suitable for forecasting the given scenario
- E.g. was the estimation scenario substantially different in scope?
- Also, need to consider correction of scale and recalibration of constants

Forecasting in practice

Population changes

- Real world forecasting would likely also require adjusting the sample of respondents
- We often estimate models on small samples, and then apply them to very large samples in sample enumeration
- Another key issue in forecasting is that we also need to forecast changes in the population of decision makers and in the characteristics of the choice sets they face

Forecasting in practice

Sample enumeration

- Assemble a population to use in forecasting
  - either based on real data (e.g., census), or synthetic population
  - or estimation sample
- Apply the model to this data, i.e., make a prediction for each person in that data
- Potentially incorporate weights in that process to make the sample representative
- Then aggregate demand
- If the model incorporates interactions with person characteristics, then the forecasts in sample enumeration will be different depending on those
  - this is one of the key benefits of using deterministic heterogeneity as much as possible

Insights into attribute "importance"

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Insights into attribute "importance"

Attribute importance based on utility

- Commonly used in some areas, not in others
- Compare potential range of utility impact for attributes
  - from worst to best level
- Issue
  - utility based attribute importance can be quite different from impact on probabilities/choices

Insights into attribute "importance"

Alternative approaches

- Elasticities
  - mainly relevant for labelled choices
  - only for continuous attributes
- Marginal effects/impact on probabilities
  - use entire sample
  - keep all attributes unchanged except for the one of interest
  - make two predictions at different levels for that attribute
    - e.g. best and worst level
  - compare potential impact on probabilities

Insights into attribute "importance"

Example on Covid-19 vaccine study

- Six tasks per respondent
- Choice between two vaccines or no vaccine, and between free (with wait) or paid (no wait) access
- Efficacy presented as remaining risk of infection to give respondents a baseline (for no vaccine)

Scenario 1:

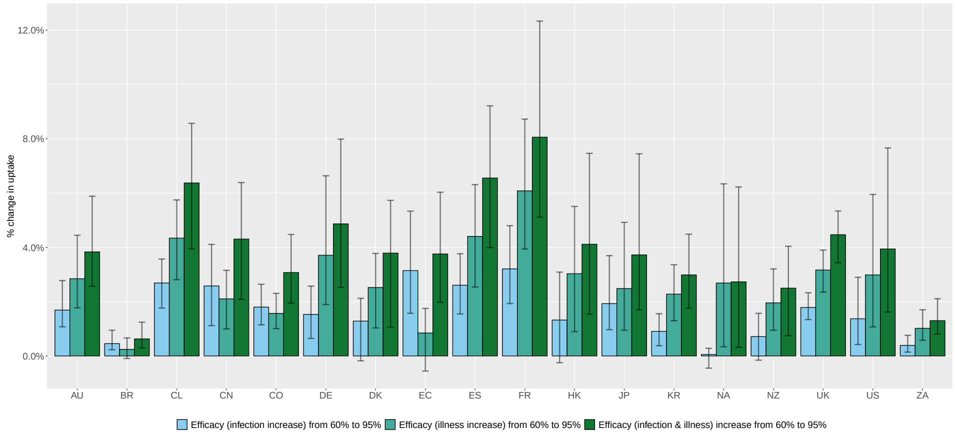
Please consider the following vaccination options and make your choice as if they happened in the current environment. Please remember there is no right or wrong answer.

	Vaccine A		Vaccine B		No vaccine
Risk of infection (out of 100,000 people coming in contact with infected person):	4,000 (4%)		3,000 (3%)		7,500 (7.5%)
Risk of serious illness (out of 100,000 people who become infected):	2,000 (2%)		4,000 (4%)		20,000 (20%)
Estimated protection duration:	five years		two years		
Risk of mild side effects (out of 100,000 vaccinated people):	100 (0.1%)		500 (0.5%)		
Risk of severe side effects (out of 100,000 vaccinated people):	1 (0.001%)		5 (0.005%)		
Population coverage:	60%				
Exemption from international travel restrictions:	restrictions apply				restrictions apply
Waiting time (free vaccination):	1 months		3 months		
Fee (no waiting time):		£100		£50	

	Vaccine A free	Vaccine A paid	Vaccine B free	Vaccine B paid	No vaccine
Your preferred choice is:	○	○	○	○	○

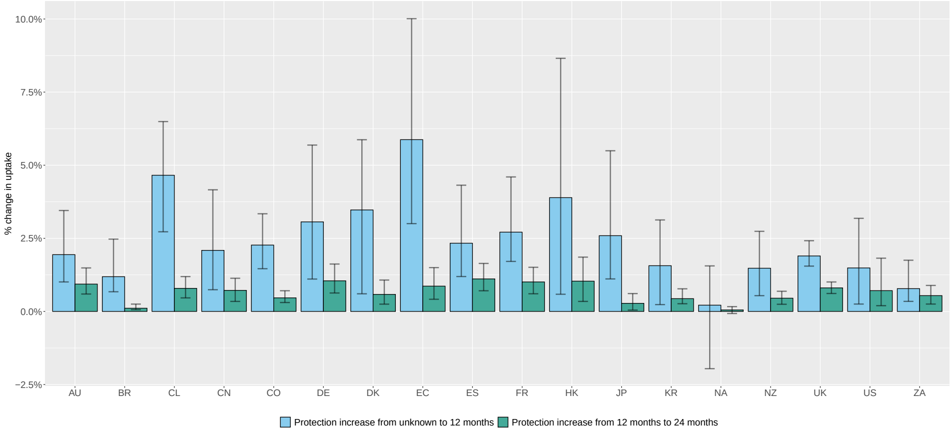
Insights into attribute "importance"

Impact of efficacy on vaccine uptake



Insights into attribute "importance"

Impact of protection duration



Insights into attribute "importance"

Impact of severe *vs* mild side effects